

**SIGNAL-STRENGTH-BASED NAVIGATION SYSTEM
FOR INDOOR WIRELESS NETWORK ENVIRONMENTS**

An Undergraduate Research Scholars Thesis

by

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ABSTRACT

Signal-Strength-Based Navigation System for Indoor Wireless Network Environments

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In this study, a particle filter used for signal processing will be designed to reduce the positional uncertainty in indoor environments where current Global Positioning Systems (GPS) are often unable to function. This study will use a wireless local area network (WLAN) composed of several access points whose signal strengths are used to compute the position of a mobile vehicle. As the vehicle begins to move forward, the change in position introduces error into the received signal, causing it deviate off course. This accumulation of error will be mitigated through the use of dynamic filtering and error estimation. A particle filter will be designed and programmed into the vehicle, decreasing the error propagation brought on by changes in position. To further decrease deviation from the instructed path, the particle filter will be modified with a feedback loop using the error for a given path orientation, which we will refer to as “path-specific error”. Using both the particle filter and path-specific error estimations, it is expected that the robot will be able to follow a given path with minimal deviation.

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CHAPTER I

INTRODUCTION

Navigation

The navigation system implemented in this study uses the principle of signal attenuation to estimate the location of the vehicle. As a radio signal propagates outward from a source, the strength and quality of the signal attenuate due to free space absorption and refraction in air, also known as path loss. For many wireless signals, the distance between a transmitter and receiver can be quantified using the Hata-Okumara model in equation (1), which relates signal power to signal propagation distance [1].

$$\log(d) = \left(\frac{1}{10n}\right) (P_{TX} - P_{RX} + G_{TX} + G_{RX} - X_a + 20\log(\lambda) - 20\log(4\pi)) \quad (1)$$

In the equation shown above, P_{TX} and P_{RX} are the transmitting and receiving power, G_{TX} and G_{RX} are the transmitting and receiving gain, X_a is a random variable, λ is the signal wavelength, n a constant that accounts for obstacles, and d is the propagation distance. Because many of these vary due to environmental factors, the navigation model used in this study will use the simplified model in equation (2).

$$A \cdot \log(d) + B = P_{RX} \quad (2)$$

The coefficients A and B are found using by measuring the received power at multiple distances and using least squares regression.

Many navigation systems utilize the principle of trilateration to localize a vehicle with respect to a point of reference. The navigation system developed in this study uses the simplified Hata-Okumara model in conjunction with trilateration to estimate the location of the vehicle with respect to its initial position. The three reference signals necessary for trilateration are provided by three stationary wireless transmitters that continually send data packets to the mobile vehicle. By measuring the strength of signal received from each transmitter, the simplified signal strength model is used to estimate the position of the vehicle relative to each transmitter. If given the location of the transmitters with respect to the vehicle's initial position, the intersection of these positions can be found using trilateration, allowing the current location of the vehicle to be estimated.

Particle filter

In signal processing, filtering is the process by which measurements meeting a certain criteria are separated from other measurements in order to provide a better estimate of the state of a system [2]. The process of filtering is used in a variety of applications where analytical estimation techniques are inadequate, such as in localization with noisy data sets.

In this study, filtering will be used to provide an improved estimate of the state of a system from a set of randomly distributed data. One common method for determining the state from a set of measurements is the standard particle filter. A particle filter relies on randomly generated data

called particles—coordinates that represents a possible state. In essence, a particle is an estimate of the state of a system. The implementation of a particle filter involves two distinct steps: creation of a randomly distributed particle field and the selective filtering of particles based on a measurement, in this case the received signal strength indicator (RSSI). These two steps are then repeated for subsequent state variable estimates.

The filtering used in particle filters relies on applying a probabilistic distribution to a set of randomly generated particles by using the obtained measurement to construct the filtering criteria. These criteria are designed to eliminate particles that are statistically unlikely to represent the true state of the system. For each iteration of the particle filter, a new batch of particles is generated and selection criteria are created using the current measurement. In the next and final phase, particles that do not meet these criteria are then eliminated from the distribution. In this way the remaining distribution of particles converges to the system's actual state.

CHAPTER II

METHODS

Signal trilateration

Trilateration is a method commonly used for determining the geospatial location of an object. The process of trilateration requires the measurement of three or more distances from previously known locations. For the mobile robot used in this study, these distances are obtained by measuring the RSSI of data packets received from three different radio transmitters. The radio transmitters (beacons) remain stationary while continuously transmitting data packets to a receiver onboard the robot. As the robot's position relative to the beacons changes, the signal strength of the transmitted data packets change accordingly. The distances between the beacons and the robot are found by using the RSSI values in conjunction with the Hata-Okumara method described in the introduction.

After these distances are calculated using the Hata-Okumara method, the mathematical process of trilateration is used to determine the location of the robot relative to the beacons. To solve for the location of the robot, the distances between the robot and the beaks are expressed in terms of the robot and beacon Cartesian coordinates relative to the origin [3].

$$R_i = ((x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2)^{1/2} \quad (3)$$

In the equation shown above, R_i is distance between the robot and the i^{th} beacon. The Cartesian coordinates of the robot are represented by x , y , and z , while the Cartesian coordinates of the i^{th} beacon are represented by x_i , y_i , and z_i . Because the above equation is nonlinear in terms of the unknowns, it must be transformed to a linear form that can be solved analytically. Both sides of equation (3) are squared to yield

$$R_i^2 = S_i^2 - 2xx_i - 2yy_i - 2zz_i + x^2 + y^2 + z^2 \quad (4)$$

where

$$S_i^2 = x_i^2 + y_i^2 + z_i^2 \quad (5)$$

Due to the final three terms in equation (4), the equation is still nonlinear in the unknowns. To make the equation linear, these terms are converted to a known value, $S_2^2 - S_1^2$, value by subtracting the quantity R_1^2 from both sides

$$R_i^2 - R_1^2 = S_2^2 - S_1^2 - 2xx_{i1} - 2yy_{i1} - 2zz_{i1} \quad \text{for } i = 2,3 \quad (6)$$

where

$$x_{i1} = x_i - x_1$$

$$y_{i1} = y_i - y_1 \quad (7)$$

$$z_{i1} = z_i - z_1$$

Using equations (6) and (8), a system of linear equations can be written in matrix form in terms of the unknown coordinates

$$\mathbf{W}\mathbf{r}_h = \boldsymbol{\beta} - \mathbf{d}z \quad (8)$$

$$\begin{aligned} \boldsymbol{\beta} &= \begin{bmatrix} \beta_2^2 \\ \beta_3^2 \end{bmatrix} & \mathbf{r}_h &= \begin{bmatrix} x \\ y \end{bmatrix} \\ \mathbf{d} &= \begin{bmatrix} z_{21} \\ z_{31} \end{bmatrix} & \mathbf{W} &= \begin{bmatrix} x_{21} & y_{21} \\ x_{31} & y_{31} \end{bmatrix} \end{aligned} \quad (9)$$

where

$$\beta_i^2 = (R_1^2 - R_i^2 - S_1^2 + S_i^2)/2$$

The unknowns in \mathbf{r}_h are isolated by taking the inverse \mathbf{W}^{-1} on both sides

$$\mathbf{r}_h = \mathbf{W}^{-1}[\boldsymbol{\beta} - \mathbf{d}z] \quad (10)$$

Particle filter

An essential component to the navigation system used in this study is the particle filter, which uses the filtering and regeneration of particles based on probability to provide the robot with an estimate of its current location. The filtering of the particles relies on two key measurements: The reference data and the standard error. The process of obtaining both of these values begins by taking several sample RSSI values from each beacon. The mean of each sample group of

RSSI values is determined and used to estimate the robot's location (reference data) using trilateration. The standard error of each RSSI group is also computed, which is then converted to a distance using the Hata-Okumara formula. The reference data is used in conjunction with the standard error to filter particles that are not located within the standard error of the reference data. The particles that remain, which are the most likely estimates of the robot's true location, are kept for the next iteration.

After the filtering of the unwanted particles, new particles must be regenerated in a process called resampling. The resampling of particles must take into account several factors including the location of the remaining particles, the number of remaining particles, and the predicted motion of the robot. The remaining particles that survived the first filtering are used to resample new particles, since these represent the most likely estimates of the robots true position. To ensure that the resampled particles are as equally likely estimates, the new particles are generated within the vicinity of the surviving particles. In this study, the number of resampled particles will be the same as the number of particles that were filtered. This additional requirement ensures a steady number of particles for each iteration, avoiding the excessive filtering or resampling of particles.

Control system

Thus far, only the signal trilateration and particle filter modules have been introduced; however, the ability to determine the robot's position is not singularly sufficient for navigation in a WLAN environment; a decision-making navigation and control module (NCM) is also necessary.

The NCM takes position measurement data from the particle filter and by comparing it to the reference desired position, determines the physical actions that must be taken by the robot's onboard motor in order to navigate towards the reference position. The NCM is implemented via an Arduino® interrupt model wherein the robot continually tracks changes in its position status via RSSI values, performs vector subtraction on its current position and the reference positions and then orients its motions along the resulting vector. The implementation also includes integrative error checking and derivative error prediction to achieve fluid, accurate motion towards its intended target. Integrative error checking consists of continually summing the current error with the total error over time such that steady-state error is eliminated. Derivative error prediction takes the rate in the change of error and uses it to determine if the system is in a runaway error state and then informs the navigation model. Figure 1 shows the NCM as a key component of an iterative process used to control the robot's navigation.

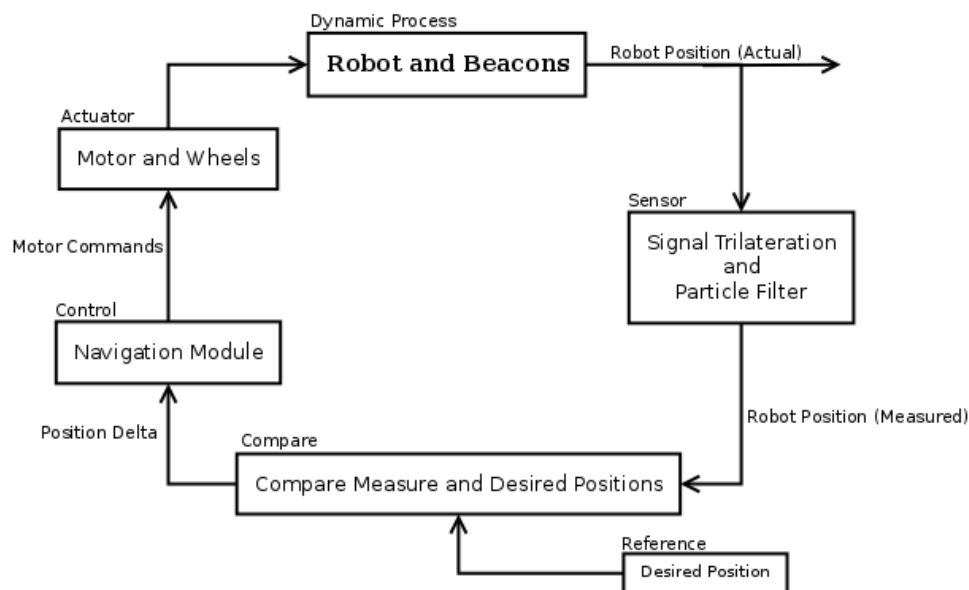


Figure 1. Navigation Process. The NCM is a key component of an iterative navigation process.

CHAPTER III

RESULTS

Software implementation

The algorithm for the particle filter used in the navigation system was implemented in the open-source, java-based language called Processing.

Testing of particle filter

The effectiveness of the particle filter was demonstrated using a combination of both computational simulation and physical testing.

Improvement to navigation

The capacity of this particle filter to provide localization correction can be easily extended to benefiting dead reckoning navigation systems.

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